UNIVERSITEIT GENT

FACULTY OF ENGINEERING AND ARCHITECTURE

Automatic Scalable Macromodel Construction for Microwave System Responses using Sequential Sampling

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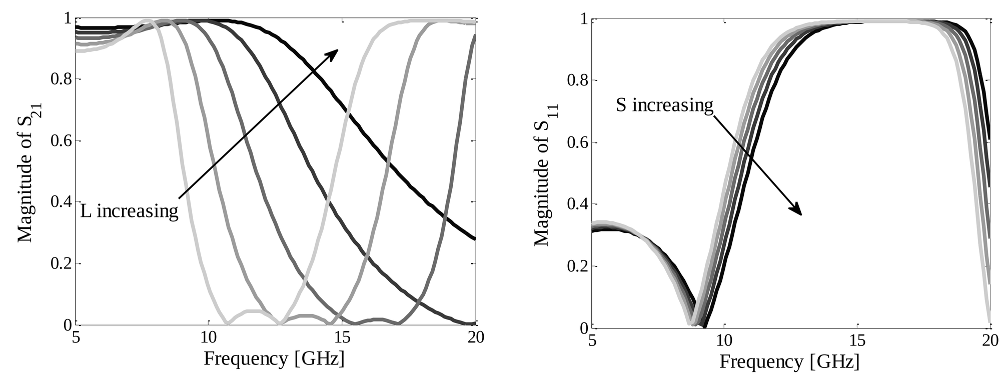
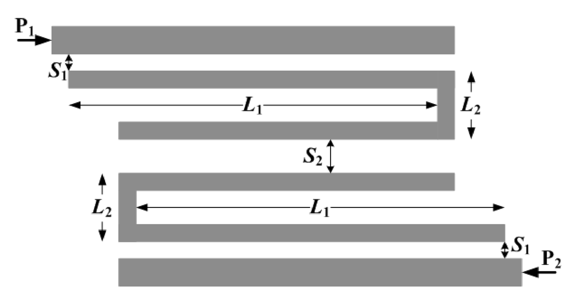
Motivation

Problem: Design of electromagnetic (EM) systems with accurate EM solvers are very expensive and state-of-the-art scalable macromodeling method can replace them in the design process. However a priori information such as the distribution of modeling samples is required in building such models which is a difficult task.

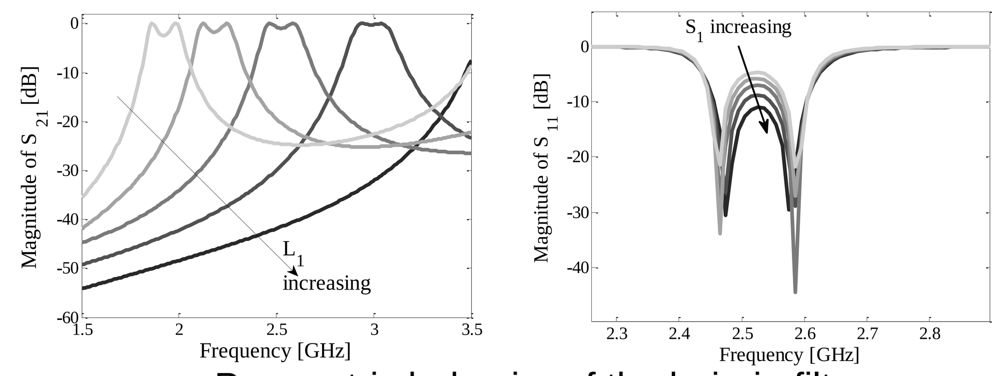
Layout of a double folded band stop filter



Parametric behavior of the folded stub filter



Layout of a hairpin band pass filter



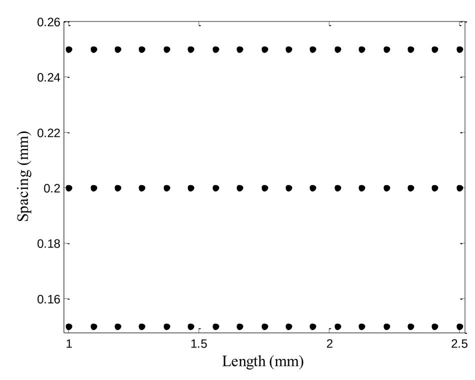
Parametric behavior of the hairpin filter

Goal: To automatically build accurate scalable macromodels with as little a priori information as possible. The final aim of this work is to generate models at the "*press of a button*".

Strategy: Selecting the modeling samples based on error criteria to find highly dynamic regions of the design space while preserving the properties of the macromodel such as stability and passivity.

Results

Example I: Folded stub band stop filter

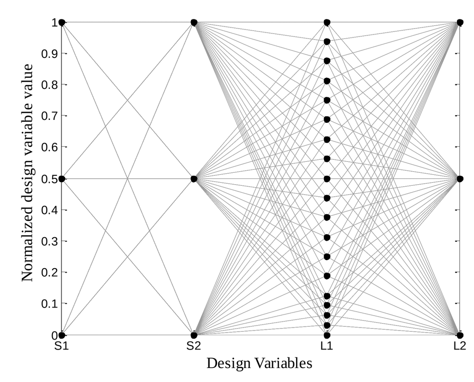


Final design space samples

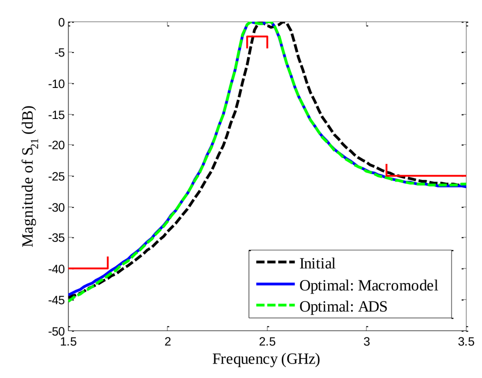
Observations:

- Length parameter is much more influential than the spacing.
- A uniform sampling is not suitable.
- Stable and passive: a dense sweep over the design space of the macromodel shows poles in the left half of the S-plane with unity bounded H-infinity norm.

Example II: Hairpin band pass filter



Final design space samples in parallel coordinate plot



Hairpin filter optimization

Observations:

- The parameter L_1 is the most influential.

Design optimization:

- The scalable macromodel is further used in the filter design.
- A single EM solver simulation costs **145** seconds but with scalable macromodel it is just **0.29** seconds.
- Considerable speedup in the design.

Multiple optimization scenarios with scalable macromodel

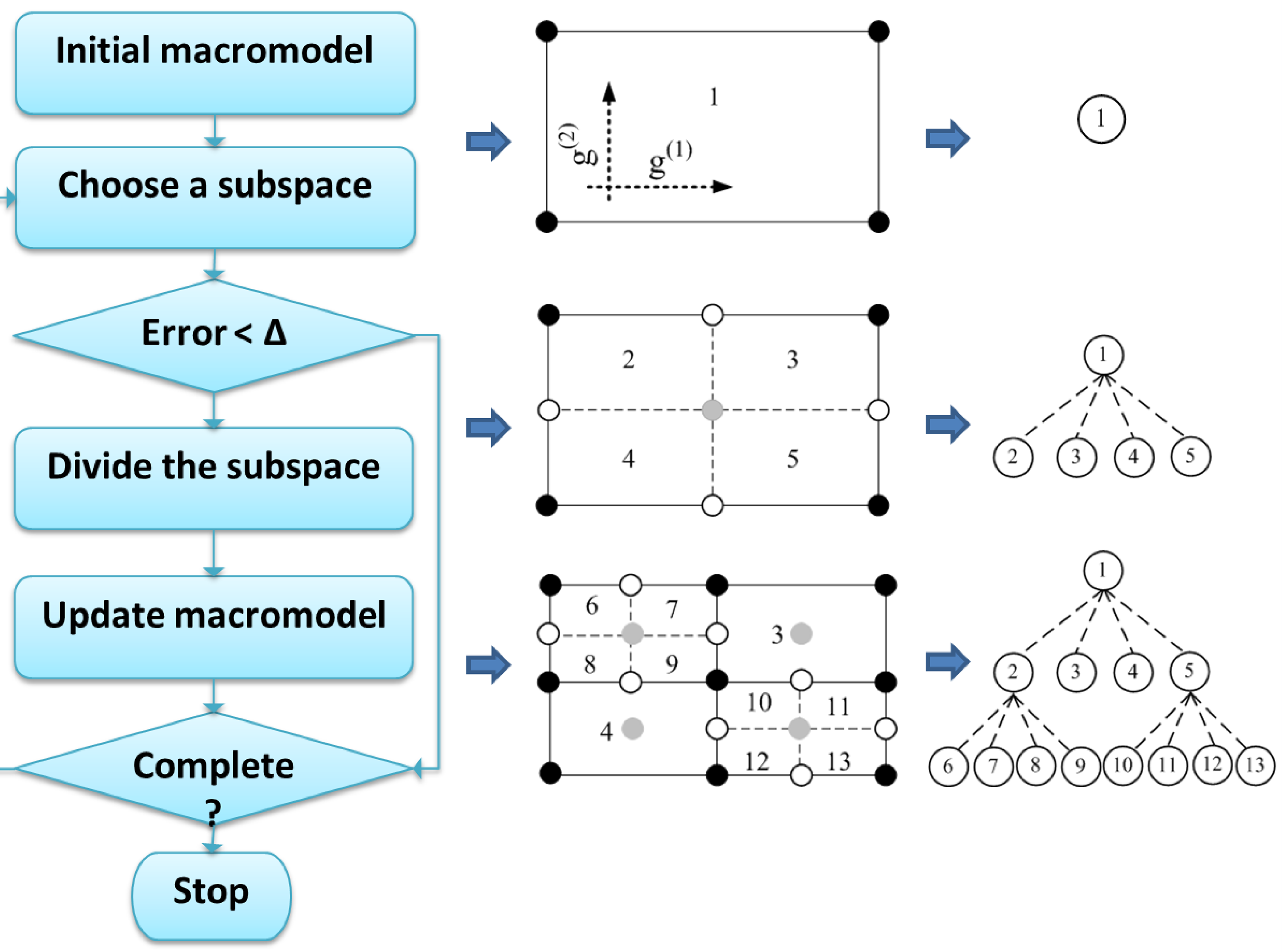
Initial Design Point (S_1, S_2, L_1, L_2) [mm]	Optimal Design Point $(S_1^*, S_2^*, L_1^*, L_2^*)$ [mm]	# Function Evaluations	Optimal Cost	Processor Time [sec]
$[0.30, 0.70, 12.00, 3.00]$	$[0.27, 0.75, 12.10, 3.25]$	538	-8.4×10^{-4}	200.29
$[0.34, 0.69, 14.10, 2.90]$	$[0.28, 0.75, 12.19, 3.20]$	444	-6.3×10^{-4}	139.80
$[0.33, 0.68, 11.50, 3.20]$	$[0.28, 0.75, 12.10, 3.24]$	353	-10.9×10^{-4}	107.82

Tree-based sequential sampling

Important features:

- Error-based division.
- Searches for highly dynamic regions.
- Passivity and stability can be guaranteed.
- Sampling over the parameter space.
- independent branches for different regions.

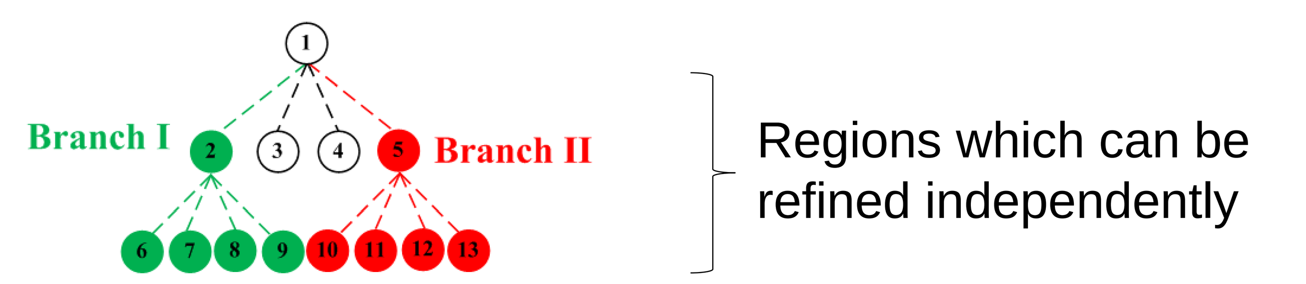
Algorithm:



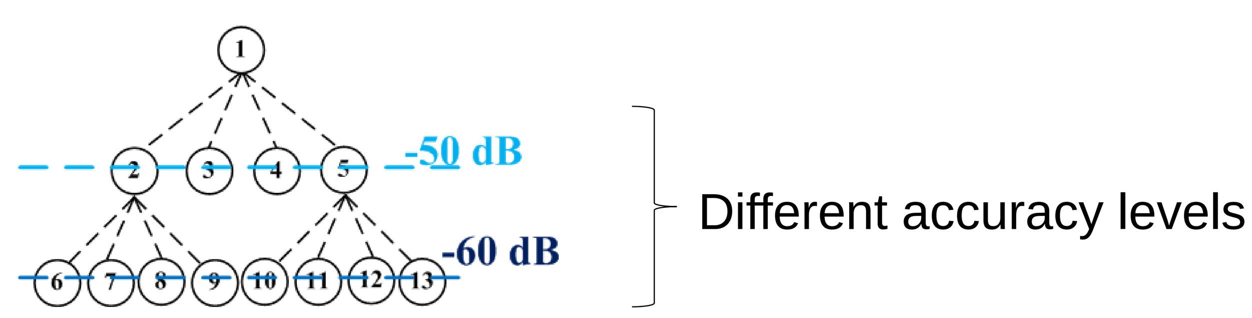
Conclusions

Advantages:

1. Considerable automation:
   i. Less burden on the designer.
   ii. No need of a priori information before modeling.
2. Tree-based implementation:
   i. Parallel processing possible.



3. Error-based division and refinement:
   i. Multi-fidelity models can be created.
   ii. Human-in-the-loop is possible.



4. Properties such as stability and passivity can be guaranteed based on the scalable macromodeling method used.

Possible future directions:

1. Extending to scattered grids and further reducing the complexity.
2. Avoiding expensive EM simulations for validation.